Centralized or Decentralized? An Empirical Model on Task Assignment of Government in Pandemics

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Motivation: Task Assignment in Pandemic

- During the spread of COVID-19, designing, imposing and lifting mitigation policy has been the center of discussion.
- Two important observations:
  - Mitigation policies have geographical externalities.
  - Mitigation policies are issued either by subnational government (China, US etc.) or central government (Germany, Singapore etc.)
- **Question:** Should mitigation policy be a Centralized or Decentralized decision?

Motivation: Task Assignment in Pandemic

- Task assignment of government (Oates, 1972):
  - Centralization internalizes externalities while decentralization respects heterogeneity.
- We revisit this famous intuition by analyzing the task assignment problem of government in pandemics.
- What's new conceptually?
  - Fighting with pandemic is a dynamic task, i.e. focusing on the timing of mitigation policy.
  - We introduce new channels that may mediate the classical intuition.

This Paper

- We write down a dynamic game model of regional government's decision on mitigation policy.
  - Regional authorities trade off between cost of economy, value of lives and political concerns based on regional characteristics.
  - But they did not taking into consideration of the externalities.
- 2 important factors that could affect their decision:
  - Regional differences in value system, e.g. political attitude, electoral concerns etc. (Barrios and Hochberg 2020., Allcott et al. 2020.)
  - Differences of regional economic indicators, e.g. unemployment and consumer expenditure, etc.

This Paper (CONT')

- We estimate the models using the observed lock-down timing and cases/deaths data of COVID-19, social-distancing metrics and Macro data in the US.
  - Step 1: Estimate a structural SIR model with regional spillover.
  - Step 2: Estimate a dynamic game model to find decision-related parameters.
- The policy experiments that we are interested in are:
  - Optimal timing of lock-down and reopening decision made by encompassing externalities.
  - Is it better for federal government to design the timing of mitigation policy?

Related Literature

Our paper is closely related to literature on COVID-19, public good and externalities, and dynamic game.

- Literature on epidemics, pandemics and COVID-19:
  - Structural estimation of SIR model. (Atkeson et al. 2020; Fernández-Villaverde and Jones 2020; Berger et al 2020; Eichenbaum et al 2020; Piguillem and shi 2020)
    We extended classic SIR model with spillover effects.
  - Strategies/effectiveness of lock-down/mitigation policies. (Acemoglu et al. 2020 Alvarez et al.2020; Fang et al. 2020; Jones et al 2020)
    We estimate a dynamic game between local governments.
    We also construct counterfactuals based on estimation results to reveal the effectiveness of mitigation policies.
  - Estimation of epidemiological parameters. (Manski and Molinari 2020)
    We make use of these bounds in our structural SIR simulation.

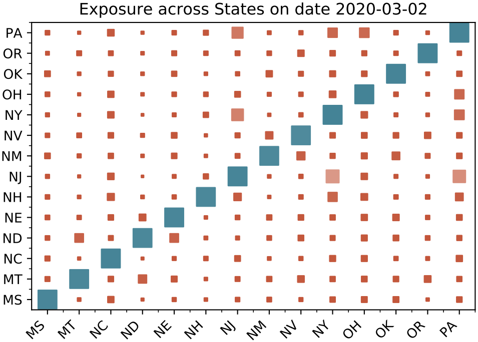
Related Literature

- The classical literature of public good and its externalities:
  - Task assignment of government (Oates et al. 1972; Banzhaf and Chupp. 2012; Kuwayama and Brozović. 2013; Knight. 2013)
    Our model makes it possible for us to evaluate the welfare implication of various counterfactual task assignments.
- The estimation method we adopt is from the literature of empirical estimation of dynamic game. (Aguirregabiria and Mira. 2007; Bajari, Benkard, Levin. 2007; Pakes et al 2007; Sweeting 2012; Ryan 2012)

Data

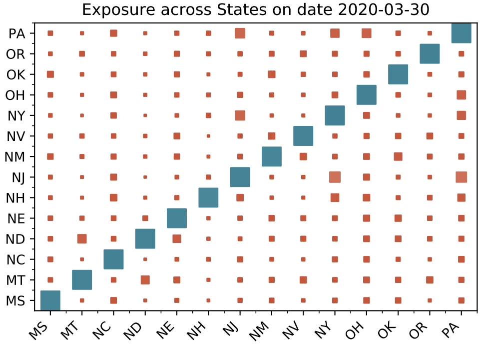
- Footage data:
  - PlaceIQ: We use this well-constructed LEX index as an alternative to test robustness
  - Safegraph: Daily phone tracking data accurate to the nearest census block group
- Epidemiological data:
  - We use the tested, confirmed and death data from The COVID Tracking Project.
- Economic Indicators:
  - The economic indicators that we use are from The Opportunity Insights Economic Tracker program
- Government Interventions:
  - We collect the dates on interventions via online announcements

Empirical Evidence 1: Inter-state Exposure

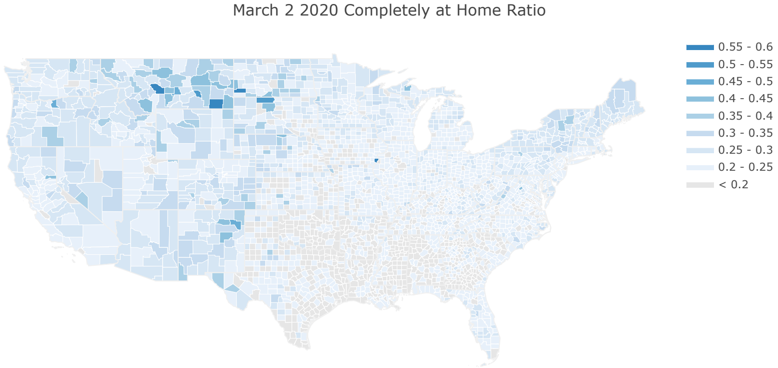


$$\text{Daily } LEX_{ij} = \frac{\#\text{devices pinned in state i in the past 14 days among denominator}}{\#\text{devices pinned in state j today}}$$

Empirical Evidence 1: Inter-state Exposure

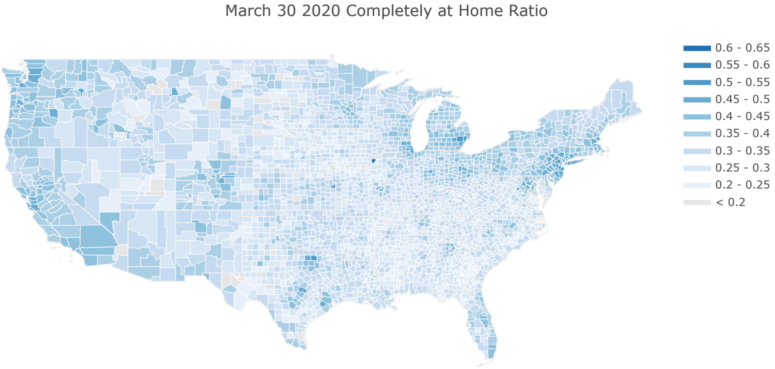


Empirical Evidence 2: Social Distancing

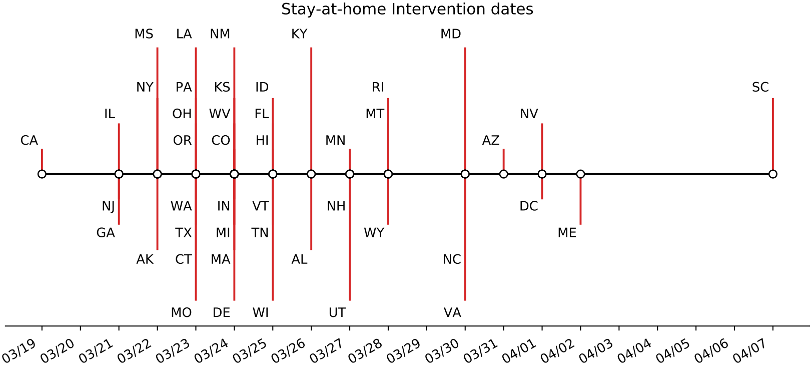


- Data from SafeGraph: This ratio is measured by the share of mobile devices which did not leave home.

Empirical Evidence 2: Social Distancing



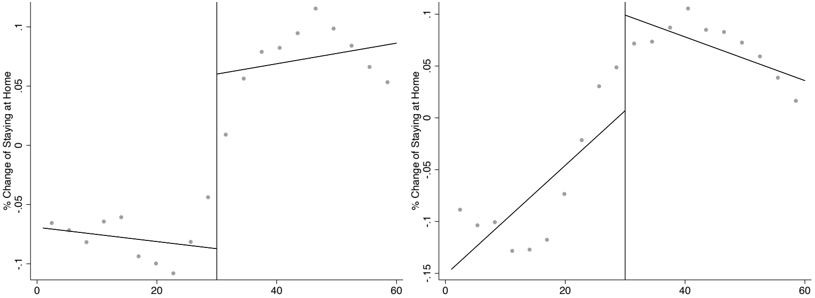
Empirical Evidence 3: Intervention timeline



Empirical Evidence 3: Event Study

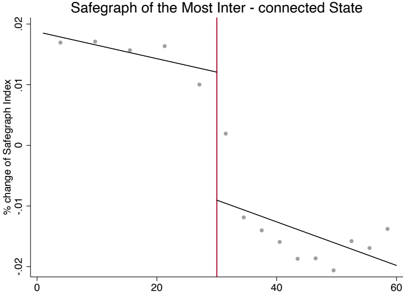
- To show the effect of state government's mitigation policy, we plot % change of activity around the time of different mitigation policies.
- The outcome variables are change of stay-at-home ratio & inter-state activity.
  - We control for confirmed cases to capture voluntary activity reduction.
  - Other controls include state fixed effect, the effect of each day of a week and holidays.
- We also conduct a falsification test to show that state m's mitigation policy does not affect the movement from state m' to m.

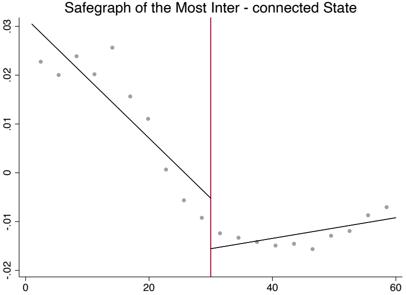
Empirical Evidence 3: Event study



- Left: First state intervention.
- Right: Stay-at-home order

Empirical Evidence 3: Event study





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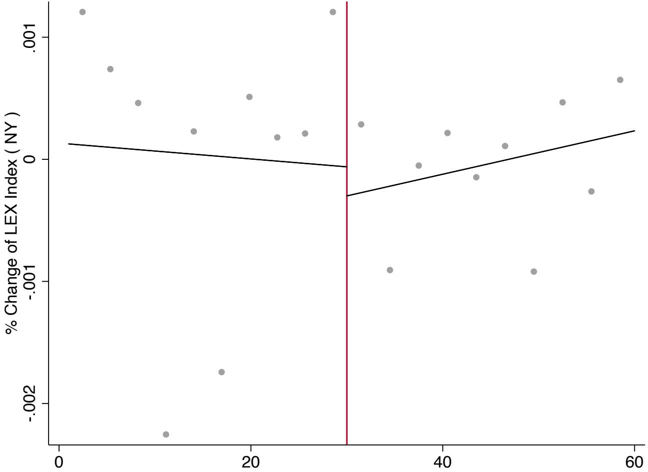


- Falsification test.

Model Setup: Basics

- Time is discrete. Everyone in the economy discounts future by the same δ.
- There are M heterogeneous regions, $m \in \{1, 2, 3, ...M\}$.
- At each point of time t, each region has a population of n_t^m. $n_t = \sum_r^M n_t^m$. The initial population is n^m and n respectively
- $\forall t$, each individual in each m can be one of the 4 types:
  - Susceptible s_t^m, infected i_t^m, dead d_t^m or recovered r_t^m.

Model Setup: COVID-19 related States

- Susceptible (s_t^m): individuals that have not been exposed to the virus.
- Infected (i_t^m): individuals that are infected and are infectious.
- Recovered (r_t^m): infected individuals that have recovered have immunity thereafter.
- Dead (d_t^m): individuals that die of the disease at t.
- In each period, we have the following equality holds in each region: $1 = s_t^m + i_t^m + r_t^m + d_t^m$.

Model Setup: Action Space

- Government can impose mitigation policies on the regional economy.
- We assume that the lock-down decision is a discrete decision that has a total $L+1$ possible actions, i.e. $l_t^m \in \{0, l_1, l_2, ...l_L\}$.
- As shown in the previous reduced form analysis, we focus on the timing of 2 policies interventions: first policy issued and stay at home order.
- Currently, we focus on a set of closely connected states NY, NJ, CT, PA, DE, RI and MA.

COVID-19 State Transitions: Law of Motion

- We consider a simple SIR structure with regional spillover effect.

$$\Delta s_{t+1}^m = -\lambda_{m,m}(I_t^m)\beta^m(I_t^m)\frac{s_t^m}{1-d_t^m}i_t^m - \sum_{m' \neq m}\lambda_{m,m'}(I_t^{m'})\beta^{m'}(I_t^{m'})i_t^{m'}\frac{s_t^m}{1-d_t^m}$$

$$\Delta i_{t+1}^m = \lambda_{m,m}(I_t^m)\beta^m(I_t^m)\frac{s_t^m}{1-d_t^m}i_t^m + \sum_{m' \neq m}\lambda_{m,m'}(I_t^{m'})\beta^{m'}(I_t^{m'})i_t^{m'}\frac{s_t^m}{1-d_t^m} - \gamma i_t^m$$

$$\Delta r_{t+1}^m = (1-\nu)\gamma i_t^m$$

$$\Delta d_{t+1}^m = \nu\gamma i_t^m$$

- where $\lambda_{i,m}$ is the inter-regional connection, β^m is the infection rate and γ, ν are standard COVID-19 related parameters.
- To solve the model using full-information we need to solve for a 4-variable diffusion process, which needs extra work than Ait-Sahalia (2002, 2008), and is beyond this paper.

COVID-19 State Transitions: Indirected Inference

- We consider the following regime-switching model with Weilbull function as our auxiliary model and conduct indirect inference for each m.

$$\Delta d_t = d\frac{b}{a}\left(\frac{t-t_0-c}{a}\right)^{b-1}\exp\left[-\left(\frac{t-t_0-c}{a}\right)^{b}\right]+\sigma_{k_t}\epsilon_t$$

  k_t here is the regime at time t, ϵ_t are i.i.d. and canonical Gaussian. σ_{k_t} is regime specific variances.

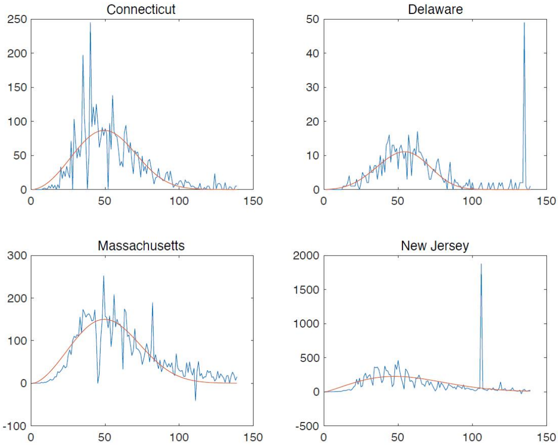
- To further use information other than d_t, we also impose bounds on model implied infected population at each period t from Manski and Molinari (2020) when conducting estimation.

Estimation Details

- Choice of parameters:
  - $\{\lambda_{m,m'}(I^m)\}$ is calibrated from Safegraph data.
  - γ is the daily rate at which agents who are infected stop being infectious. We use the median incubation period 5 from literature, that is, $\gamma = 1/5$.
  - We denote the infection-fatality rate from the disease by ν. We consider values of $\nu = 1\%$ as our baseline value and 1.4% as an alternative value.
  - Bound for sensitivity is 0.6 and 0.9, specificity is set to be 1.

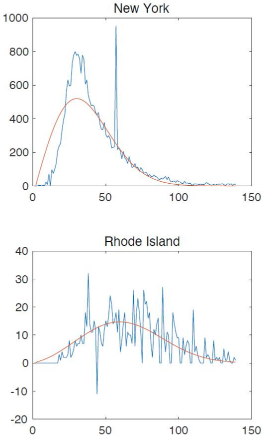
- Via indirect inference, we got estimates for $\beta^m(I)$, $\forall m$, which can be used for simulating counter-factual disease propagation.

Simulation results 1



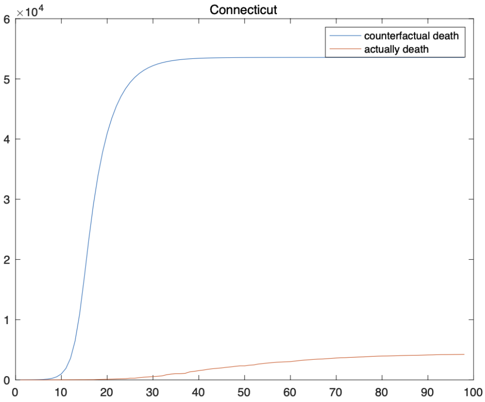
- Day 1 is March 12th.
- Red line is the simulated daily death, blue line is the actual data from The Covid-tracking Project.

Simulation results 1



- Day 1 is March 12th.
- Red line is the simulated daily death, blue line is the actual data from The Covid-tracking Project.

Simulation results 2



- Day 1 is March 14th.
- Blue line is the counterfactual death toll without any mitigation policy, red line is the actual accumulated deaths.

Economic State Variables

- We collect a set of economic related state variables ($\mathbf{E}_t = \{E_t^1, ..\}$). Specifically $E_t^m = \{b_t^m, u_t^m\}$ contains:
    - b_t^m is the percentage change of small business revenue.
    - u_t^m is the change of unemployment rate.
- We assume that $\mathbf{E}_t$ is affected by the COVID-19 situation, but not the other way around.
    - We parameterized the transition of $\mathbf{E}_t$ estimation of the transition density for $\mathbf{E}_t$ given COVID-19 state variables and $\mathbf{E}_{t-1}$.

Economic State Variables

- We assume that both b_t^m and u_t^m is evolved according to the following parameterized AR(1) transition density:

$$b_t^m = \rho^b b_{t-1}^m + \rho_b^z Z_t + \sum_k \rho_b^l \mathbf{1}(I^m = k) + e_t^m$$

$$u_t^m = \rho^u u_{t-1}^m + \rho_u^z Z_t + \sum_k \rho_u^l \mathbf{1}(I^m = k) + e_t^m$$

  where Z_t consists of d_t^m, $(d_t^m)^2$, Δd_t^m and $(\Delta d_t^m)^2$. e_t^m is a i.i.d. $N(0,1)$ error.

- In practice, all state variables are logged. We pool all regions together in estimation.

- Putting together with our results on $p(\Delta \mathbf{d}_t, \mathbf{d}_t \mid \Delta \mathbf{d}_{t-1}, \mathbf{d}_{t-1}, \mathbf{L}_t)$, we have the transition density of all the state variables $p(\mathbf{X}_t | \mathbf{X}_{t-1}, \mathbf{L}_t)$.
  - The structural of our SIR model makes it sufficient to carry 2 covid state variables.

Economic State Var Transition

	(1) Ump	(2) Revenue
L.Ump	0.985***	
	(0.00248)	
L.Revenue		0.965***
		(0.00817)
L.Daily Death	0.00117	-0.0300***
	(0.00134)	(0.00630)
L.Daily Death Square	-0.000840***	0.00212***
	(0.000139)	(0.000733)
L.Cumulative Death	-0.00182	0.0297***
	(0.00136)	(0.00638)
L.Cumulative Death Square	0.000452***	-0.00127***
	(0.0000812)	(0.000427)
Mitigation Policy=1	-0.00708***	-0.0654***
	(0.00147)	(0.00767)
Mitigation Policy=2	-0.0144***	-0.0774***
	(0.00211)	(0.0121)
R-square	1	1
Observations	539	539

Table: Transition Density of Economics State Variables

Dynamic Game: Per-period Payoffs

- The per-period payoff of regional government is described as below:

$$\pi(\mathbf{L}_t, \mathbf{X}_t, \xi_i^m) = \pi^p(E_t^m, d_t^m, \zeta^m, l_t^m) + \xi_t^m$$

- where $\xi_t^m \sim N(0,1)$ is a choice specific i.i.d. random shock

$$\pi^p(E_t^m, d_t^m, \zeta^m, l_t^m) = \underbrace{\theta_e' E_t^m}_{\text{economic cost}} + \underbrace{\theta_d' f(d_t^m)}_{\text{loss of lives}} + \underbrace{\zeta^m \sum_i^L \theta_p^{i\prime} \mathbf{1}\{l_t^m = l_i\}}_{\text{political cost}}$$

  - f is a polynomial up to the 2nd order.
  - There is a m specific cost of implementing policy, where ζ^m is the share of voters in m that voted for Trump during the 2016 pesidential election. (Allcott et al.2020)

Dynamic Game: Equilibrium

- We focus on Markov Perfect Equilibrium, i.e. given a same state $\mathbf{X}_t, \xi^m$, player m make same choices over time.
- Follow the BBL, we assume the data observed are generated by a single MPE profile $\mathbf{L}$.
- Per-period payoff function $\pi(\mathbf{L}_t, \mathbf{X}_t, \xi_i^m)$ satisfies the Monotone Choice assumption. So we can estimate $Pr(I_t^m|\mathbf{X}_t)$ given the distribution knowledge of ξ_t^m.

Dynamic Game: CCP Estimation

- We estimate the policy function using the ordered-Probit model.
  - The dependent variable is the observed policy choice for each day, which is chosen from an ordered set $\{0, FSA, SAH\}$.
  - Explanatory variables are (logged): e_t^m, u_t^m, Δd_t^m, $(\Delta d_t^m)^2$, d_t^m, $\sum_{m' \neq m} \Delta d_t^{m'}$, $(\sum_{m' \neq m} \Delta d_t^{m'})^2$, $\sum_{m' \neq m} d_t^{m'}$.
- Other regions' state variables are grouped together when enter the policy function of region m, following Ryan (2012).

CCP Estimation

	Mitigation Policy
Ump	36.12**
	(14.49)
Revenue	-0.424
	(1.974)
Daily Death	2.273
	(2.230)
l_daily_death_2	0.273***
	(0.0737)
Cumulative Death	-2.174
	(2.192)
Sum Daily Death	-17.07***
	(5.830)
Sum Daily Death Square	1.228***
	(0.353)
Sum Cumulative Death	8.601**
	(3.710)
cut1	
Constant	-11.18**
	(5.452)
cut2	
Constant	-0.196
	(4.720)
R-square	0.915
Observations	546

Table: Estimation of CCP

Dynamic Game: Value Function Approximation

- We approximate value function through forward simulation a la BBL.
- Let $V(\mathbf{X}; \mathbf{L}; \theta)$ denote the value function of firm i at state $\mathbf{X}$, where Markov strategy $\mathbf{L}$ is used by all m.

$$V(\mathbf{X}; \mathbf{L}; \theta) = \mathbb{E}\left[\sum_{t=0}^{T} \beta^t \pi\left(\mathbf{L}(\mathbf{X}_t, \xi_t), \mathbf{X}_t, \xi_t^m; \theta)\right) |\mathbf{X}_0 = \mathbf{X}; \theta\right]$$

where T and β should be chosen s.t. value function after T periods is sufficiently small, e.g. $\beta = 0.98$ and $T = 120$.

Dynamic Game: Value Function Approximation

- Then we could do the simulation of VF for 546 unique state realizations observed in the data.
- A single simulated path of play can be obtained by the following:
  1. Starting at state $\mathbf{X}_0 = \mathbf{X}$, draw private shock ξ_o^m from $N(0,1)$ for each m.
  2. Pick an action l_0^m from any Markov strategy profile $\mathbf{L}(\mathbf{X}_0, \xi_0)$ (or any other deviations of it) and the resulting profits $\pi\left(\mathbf{L}(\mathbf{X}_0, \xi_0), \mathbf{X}_0, \xi_0^m; \theta\right)$.
  3. Draw a new state $\mathbf{X}_1$ using the estimated transition density $\mathbf{P}$.
  4. Repeat above steps for T periods.

  We averaging G different paths of play to obtain a estimate of $V(\mathbf{X}; \mathbf{L}; \theta)$ given any strategy profiles.
- Notice that we can use the linearity simplification because the way θ enters into the profit function.

Dynamic Game: Equilibrium and "BBL" Estimator

- The strategy profile $\mathbf{L}$ is a MPE if and only if $\forall m$, $\forall \mathbf{X}$, and $\forall$ alternative Markov policies $l^{'}$,

$$V\left(\mathbf{X}; l', \mathbf{L}_{-m}; \theta\right) \leq V\left(\mathbf{X}; l, \mathbf{L}_{-m}; \theta\right)$$

- Thus we can form the following estimator ("BBL" Estimator)

$$\hat{\theta}^{BBL} = \underset{\theta}{\text{argmin}} \sum_{\mathbf{X}} \sum_{l'} \max\{\left(V\left(\mathbf{X}; l', \mathbf{L}_{-m}; \theta\right) - V\left(\mathbf{X}; l, \mathbf{L}_{-m}; \theta\right)\right)^2, 0\}$$

To obtain a reasonable estimator, we need to think carefully about the potential deviation strategy l'.

Dynamic Game: Moment Ineq Based Estimator

- Alternatively, we could construct a moment inequality based estimator ('MI Estimator"), where the moment inequality is of the form

$$\sum_{\mathbf{X}} V\left(\mathbf{X}; l', \mathbf{L}_{-m}; \theta\right) - V\left(\mathbf{X}; l, \mathbf{L}_{-m}; \theta\right) \leq 0$$

  for an alternative strategy l'.

- According to Sweeting (2013), the estimates from above 2 estimators are sensitive to the choice of alternative strategies.

Dynamic Game: GMM Estimator

- We could also construct GMM estimator by the following steps:
  1. When simulating a single path of play, approximate $V(\mathbf{X}; I, \mathbf{L}_{-m}; \theta)$ for all $I = 0, I^1, I^2$ and then find the I that maximizes the object.
  2. Simulate for G path and then calculate probability of chosing each choice 0 I_1 and I_2 based on the simulation results, denote it as vector $\hat{I}(\mathbf{X})$.
  3. Find the θ that minimizes the simulation based CCP and actual choice vector $I^{data}(\mathbf{X})$ observed in data.
- More formally, the GMM estimator is

$$\theta^{GMM} = \underset{\theta}{\text{argmin}} \sum_{\mathbf{X}} \left[\hat{I}(\mathbf{X}) - I^{data}(\mathbf{X})\right]' \left[\hat{I}(\mathbf{X}) - I^{data}(\mathbf{X})\right]$$

Counter-factual 1: Optimal Timing

- Social planner seeks to minimize the present discounted loss described as below:

$$\min_{l_t^m \in \{0, l_1, \ldots l_L\}} \quad \sum_{t=0}^{\infty} \delta^t \left[\sum_m \frac{n^m}{n} \pi^p(E_t^m, d_t^m, \zeta^m, l_t^m) \right]$$

- where

$$\pi^p(E_t^m, d_t^m, \zeta^m, l_t^m) = \hat{\theta}'_e E_t^m + \hat{\theta}'_d f(d_t^m) + \zeta^m \sum_i^L \hat{\theta}^i_p \mathbf{1}\{l_t^m = l_i\}$$

  - $\hat{\theta}'_e$, $\hat{\theta}'_d$ and $\hat{\theta}^i_p$ are estimates from the previous estimation step.
  - We seek to solve this single player dynamic problem and find the CCP that minimizes the PDV.

Counter-factual 2: Federal Decision Making

- Federal government seeks to minimize the present discounted loss described as below:

$$\min_{l_t^m \in \{0, l_1, \ldots l_L\}} \quad \sum_{t=0}^{\infty} \delta^t \left[\pi^f (E_t^m, d_t^m, \zeta, l_t^m) \right]$$

- where

$$\pi^f (E_t^m, d_t^m, \zeta, l_t^m) = \hat{\theta}'_e \sum_m \frac{n^m}{n} E_t^m + \hat{\theta}'_d \sum_m \frac{n^m}{n} f(d_t^m) + \zeta \sum_i^L \hat{\theta}_p^i \mathbf{1}\{l_t^m = l_i\} \tag{1}$$

  - $\hat{\theta}'_e$, $\hat{\theta}'_d$ and $\hat{\theta}_p^i$ are estimates from the previous estimation step.
  - ζ is the share of voters in M regions that voted for Trump in 2016 presidential election.
  - We seek to solve this single player dynamic problem and find the CCP that minimizes the PDV.

Working in progress

- We are now at the stage of estimating the transition density of $p(\mathbf{X}' \mid \mathbf{X}, \mathbf{L})$
  - We have a closed form for transition of $(\mathbf{i}', \mathbf{d}')$ conditional on $(\mathbf{i}, \mathbf{d}, \mathbf{L})$
  - Need to (non)parametrically estimate $p(\mathbf{E}' \mid \mathbf{E}, \mathbf{i}, \mathbf{d}, \mathbf{L})$
  - Curse of dimensionality
- What rules should be used to determine number of grid when we discretize the state variables?

Feedback

- Please give us feedback on:
  - Modeling choices
  - Estimation strategies
  - Literature
- Any other advice are appreciated!
- **Thank you!**